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Does Farm Income Enhance Green Productivity? Evidence from China's Rice Farming*

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This study finds that the one-period lagged income of China's rice farmers, as measured by net profit, has a significant linear negative impact (inhibitory effect) on rice green total factor productivity (RGTFP), a relationship characterized by two separate single-threshold effects. Against the backdrop of escalating global climate shocks and prominent agricultural ecological issues, the ambiguity of this driving mechanism has constrained in-depth research on the green transition of rice farming. Based on panel data from 22 major rice-producing provinces in China from 2005 to 2022, our analysis using dynamic panel models (to account for time-lag effects) and threshold models (to identify non-linear shifts) reveals that for each unit increase in net profit, RGTFP decreases by an average of 0.14%. A one-period lagged farmer income threshold is identified at 857.4 CNY/ha; the negative impact is strongest in the low-income regime (below the threshold), but becomes an insignificant positive effect after crossing the threshold. Furthermore, a mechanization level threshold exists at 6.14 kW/ha; no significant impact is observed in the low-mechanization regime, whereas the impact of lagged farmer income on RGTFP turns significantly positive after surpassing this threshold. This research provides empirical support for policy adjustments aimed at fostering a green agricultural transition.

Keywords: Farmer Income, Rice Green Total Factor Productivity, Threshold Effect, Dynamic Panel

JEL Classification: O13, Q56, C24

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I. Introduction

Amidst the growing impact of adverse global climate shocks and prominent ecological challenges (Song et al., 2022), sustainable agricultural development has become a critical issue for ensuring global food security and ecological balance. As the staple food for over half the world's population (Badoni et al., 2024), rice production carries profound environmental, economic, and social implications (Yuan et al., 2021). Traditional rice cultivation methods are often resource-intensive, characterized by extensive water irrigation and the excessive application of chemical fertilizers and pesticides. This practice not only leads to severe environmental problems such as water eutrophication, soil degradation, and increased greenhouse gas (GHG) emissions but also threatens the long-term sustainability of the agricultural system (Li et al., 2023; Qian et al., 2023; Mohd Nizam et al., 2023). As the world's largest producer and consumer of rice, China is significantly affected by these challenges (Fang et al., 2024). Consequently, promoting a green transformation in China's rice production—that is, ensuring food supply while reducing negative environmental externalities and improving resource use efficiency—has become a focal point for both government and academia.

In this context, scholars have developed a comprehensive metric: green total factor productivity (GTFP). GTFP is an indicator designed to evaluate the efficiency and quality of input factor utilization by incorporating constraints such as energy, resources, and the ecological environment; it reflects a region's capacity for resource allocation, environmental governance, and sustainable development (Liu and Xin, 2019). It moves beyond the limitations of traditional total factor productivity (TFP), which focuses solely on economic output, by incorporating “undesirable outputs” like environmental pollution and resource consumption into its accounting framework. This allows for a more comprehensive assessment of economic sustainability. In recent years, researchers have effectively measured agricultural and rice GTFP (RGTFP) and explored the influence of various macro-level factors (Yu et al., 2022; Huang et al., 2022; Nodin et al., 2023). However, the existing literature has paid insufficient attention to the impact of the economic behavior of a crucial micro-level agent: the rice farmer. As the direct decision-makers and practitioners in agriculture, farmers' choices regarding technology adoption, factor inputs, and cultivation management directly determine the economic and ecological outcomes of rice production. The core driver of these decisions is, undoubtedly, farmer income. From an economic perspective, rice

farmers are rational agents whose primary objective is profit maximization (Khan et al., 2022). Therefore, the level, composition, and stability of their income profoundly influence their trade-offs between achieving high yields and ensuring environmental protection. Stable income expectations may incentivize farmers to adopt more advanced, eco-friendly production technologies, thereby enhancing RGTFP. Conversely, if income is volatile or dependent on high-input, high-pollution methods, it may impede the green transformation process.

Although some studies have examined the income of rice farmers (Emran et al., 2021; Tran et al., 2022; Rahman et al., 2022), few have directly linked it to RGTFP to systematically investigate the specific mechanisms through which farmer income drives RGTFP. This research gap limits our understanding of the intrinsic drivers of green agricultural development and means that related policies often lack empirical support at the micro-level. Therefore, the central question of this study is: How does farmer income drive RGTFP? Specifically, we explore two aspects: First, does a higher level of farmer income directly promote or inhibit RGTFP growth? Second, does this relationship exhibit non-linear characteristics (e.g., threshold effects, where the impact shifts from negative to positive, or a U-shape, where initial income increases inhibit but higher levels promote RGTFP)? By answering these questions, this study aims to reveal the critical role of farmer income in driving the green agricultural transformation, thereby providing a scientific basis for formulating more effective and targeted agricultural support and environmental regulation policies.

This study makes two main contributions to the existing literature: (1) We construct an RGTFP accounting framework that integrates a “climate-economy-ecology” three-dimensional perspective. On the input side, we effectively control for the interference of climate factors and use monetized indicators—such as labor, land, and material and service costs—to represent the quantitative features of traditional inputs. On the output side, we simultaneously account for GHG emissions (undesirable output), carbon sequestration (desirable ecological output), and grain yield (desirable economic output). This series of methodological improvements offers a new perspective for understanding the economic attributes of RGTFP and the characteristics of producer behavior. (2) We shift the research focus down to the decision-maker by using net profit as a proxy for farmer income to investigate how it drives RGTFP. This approach not only reveals the economic logic and social roots behind farmer behavior but also provides a critical micro-level perspective for understanding and enhancing RGTFP.

II. Literature Review

Currently, the measurement of agricultural GTFP primarily relies on two categories of methods: parametric Stochastic Frontier Analysis (SFA) and non-parametric Data Envelopment Analysis (DEA). The SFA method imposes strict requirements on the functional form and, when handling multiple outputs, necessitates either their consolidation into a composite index or the use of a distance function, which can be complex and may lead to information loss (Ge et al., 2023). In contrast, DEA does not require a pre-specified functional form, offering greater flexibility in multi-input, multi-output systems and making it well-suited for simultaneously evaluating both desirable and undesirable outputs (Zhong et al., 2021). To accurately measure productivity dynamics involving undesirable outputs, scholars have introduced the directional distance function (DDF) within the DEA framework, which forms the basis for the Malmquist–Luenberger productivity index (ML index) (Chung et al., 1997). By setting a directional vector, the DDF can simultaneously expand desirable outputs while contracting undesirable outputs. However, the traditional ML index is prone to the issue of “infeasibility” in intertemporal evaluations and lacks period-over-period comparability. To address these limitations, the global Malmquist–Luenberger productivity index (GML index) was developed (Oh, 2010). By constructing a single global technology frontier that envelops all periods, the GML index mitigates the infeasibility problem and ensures that the resulting indices are intertemporally comparable. Owing to its technical advantages, the DDF-based GML index has become one of the most widely adopted frontier methods in contemporary agricultural GTFP analysis (Hamid et al., 2023; Zhang and Yu, 2025).

Once the methodological framework is established, the validity and comparability of the measurement hinge critically on the selection and definition of variables. In DEA-based agricultural GTFP research, the existing literature has widely treated GHG emissions as an undesirable output (Qin et al., 2024). More recently, some studies have begun to include carbon sinks as a desirable output to more comprehensively reflect agro-ecological performance (Shen et al., 2023; Lu et al., 2025). Concurrently, climate factors (e.g., temperature, precipitation) have been introduced as non-discretionary inputs or exogenous environmental variables to capture the influence of natural endowments on the production technology frontier (Myeki et al., 2023; Shah et al., 2024). Despite these advances, few studies have simultaneously incorporated both carbon sequestration and climate variables within the same measurement system, a gap

that is particularly pronounced in RGTFP research. Furthermore, existing RGTFP studies often employ a mix of physical quantity and monetized input indicators (Chen et al., 2019). This approach deviates from the cost-benefit perspective that increasingly dominates real-world decision-making, potentially leading to a misjudgment of producers' resource allocation efficiency. Accordingly, this paper proposes a three-dimensional "climate-economy-ecology" assessment framework for RGTFP. We incorporate both carbon sinks and climate factors into the same DEA model and replace traditional physical inputs with monetized ones, thereby achieving a more comprehensive measurement of RGTFP.

As the methodologies and variable selections for measuring agricultural GTFP have evolved, scholars have also explored its influencing factors from multiple perspectives. In research concerning rice, these factors are typically examined from three main angles: First, the optimization of input factors. Studies have shown that resource use efficiency can be enhanced by improving soil quality, optimizing water and fertilizer management, and promoting straw incorporation (Linguist et al., 2015; Jiang et al., 2017; Cao et al., 2021; Sharma et al., 2021). Capital deepening, particularly through mechanization, has also been proven to boost GTFP (Lu et al., 2024). Second, the reduction of negative environmental externalities. Adopting green production technologies is a direct path to mitigating environmental impact and raising GTFP. For example, precision agriculture techniques, such as targeted fertilization and integrated pest management (Durham and Mizik, 2021; Getahun et al., 2024), are effective methods. Similarly, ecological-circular models like organic farming and rice-duck co-culture can also effectively reduce chemical inputs and GHG emissions (Holka et al., 2022; Du et al., 2023). Third, the socioeconomic and policy environment. Several factors in this area have been found to significantly influence GTFP. These include the proliferation of agricultural production services (Xu et al., 2022), government financial support and environmental regulations (Wang et al., 2022; Shi et al., 2025), and the factor reallocation effects of urbanization (Chen et al., 2025). Furthermore, producer-specific endowments, such as their education level and farm size (Masuda, 2019; Wang et al., 2024), are also significant determinants. Although this body of research has identified a wide range of influencing factors, they all point toward a core, yet underexplored, question concerning the most direct driver of farmer decision-making: income. Therefore, the impact of farmer income on RGTFP becomes the central theme of this study.

III. Research Hypotheses

1. The Direct Influence Channel of Farmer Income

Rice farmers are rational economic agents whose fundamental objective in production is the maximization of their income (Khan et al., 2022), but their production decisions do not rely on current-period income signals. Instead, they are profoundly influenced by the lagged effect of previous-period income. In other words, previous-period income determines how farmers conduct production. Given that they have little control over market pricing mechanisms, the only viable path to increasing income is by boosting rice yields. In this context, farmers often resort to the simplest method for increasing production: the excessive application of chemical inputs such as fertilizers and pesticides to raise immediate output. Concurrently, because China's hybrid rice and its associated cultivation system have long been the driving force behind substantial yield increases (Zhu et al., 2010), farmers also tend to choose this variety for production. The former leads to distorted resource allocation and rising environmental costs, ultimately inhibiting RGTFP growth. Although the latter reduces methane (CH₄) emissions by over 30% compared to conventional rice (Smartt et al., 2018), which is beneficial for RGTFP growth, market survey data from Northeast China shows that hybrid rice seeds are typically about twice as expensive as conventional ones, influencing the choices of low-income farmers. The instability of farmer income, often caused by factors like extreme weather events, further reinforces this short-term behavior, weakening their willingness to adopt conservation tillage and green technologies and creating a path dependence on low RGTFP. Therefore, faced with the dual pressures of market risks and policy uncertainties, farmers tend to maintain traditional production models to avoid the costs of transition, further cementing a high-input, high-emission production path. Even if green technologies offer long-term income potential, their initial investment barriers and long payback periods limit farmers' motivation for adoption, especially when current subsidy policies are heavily yield-oriented. Consequently, short-term rationality driven by profit ultimately sacrifices the sustainability of the system. Thus, if an increase in previous-period net profit is not accompanied by a systemic change in production methods, it may instead intensify green efficiency losses by reinforcing existing input dependencies. Based on this, the first hypothesis of this study is proposed.

Hypothesis 1: One-period lagged farmer income has a negative short-term impact on RGTFP.

2. Threshold Effect Analysis

As previously discussed, low-income farmers often face severe capital constraints, making it difficult to bear the upfront investment costs of green production technologies (Kuang et al., 2023). At the same time, the application of green technologies may involve uncertainties in effectiveness and even risks of short-term yield reduction in the initial stages (Li and Yu, 2022). As previous-period income increases, farmers' economic capacity is strengthened, providing them with the material basis to purchase green technologies and environmentally friendly production materials, such as low-toxicity pesticides, bio-fertilizers, and precision fertilization equipment. However, this does not mean they will automatically invest this incremental income in green transition; the process has an uncertain impact on the environmental efficiency dimension of RGTFP. The key is whether farmer income has crossed the "subsistence threshold." Here, the "subsistence threshold" specifically refers to the minimum income level required for a farmer to maintain basic family living expenses (including non-discretionary consumption for clothing, food, housing, transportation, medical care, and education) and to cover core rice production costs (including unavoidable production expenditures for seeds, fertilizers, pesticides, land rent, and labor). It is the critical node where a farmer's decision-making shifts from "survival-oriented" to "sustainability-oriented." When previous-period income has not crossed this threshold, the farmer's core objective is to avoid subsistence risk by increasing short-term yields, without considering green technology investment or long-term returns. Therefore, short-term yield increase is a rational choice under subsistence constraints. Conversely, only when previous-period income consistently and stably exceeds this subsistence threshold do farmers have the prerequisite to escape the rational trap of pursuing only yield and immediate income. They gain the capacity to weigh short-term costs against long-term ecological and economic benefits, and may thus shift toward a sustainable production path that coordinates ecological protection and production efficiency. However, it must be clear that crossing this threshold only provides the possibility for green transition, not the certainty. Path dependence formed from previous high-input production, the upfront costs of green technology, market risks, and policy uncertainty may still inhibit the willingness to transition, ultimately

leading to an uncertain impact of previous-period income on RGTFP. Therefore, changes in the level of farmer income may have a non-linear effect on RGTFP by influencing their investment capacity, risk appetite, and factor allocation decisions. Thus, a threshold effect may exist for the level of farmer income itself. That is, when income is below a certain threshold, farmers are more inclined to maintain traditional production models, which come at the cost of environmental degradation and over-exploitation of natural resources (Chi et al., 2021), thus having a weak or even negative effect on RGTFP. When income exceeds the threshold, farmers are capable of investing in green technologies, but this does not guarantee they will, possibly resulting in an insignificant promotional effect on RGTFP.

Within the sample period of this study, the level of agricultural technology is primarily reflected by the level of mechanization. Its moderating role in the relationship between one-period lagged farmer income and RGTFP is, in essence, achieved through a threshold effect based on the technology's enabling role for green production. Whether the technology level breaks a critical threshold directly determines the path and effectiveness of converting lagged income into RGTFP improvements. The growth in lagged farmer income provides the economic foundation for transforming the production model, but whether this incremental income can be channeled into RGTFP enhancement depends critically on the constraints on technology application capacity imposed by the mechanization level. When the technology level is in the low-threshold regime, farmers lack the support of a modern mechanization platform, making it difficult to implement green technologies centered on precision fertilization, ecological tillage, and pollution reduction (e.g., smart agricultural machinery, mechanized ecological control equipment). At this stage, farmers' rational decisions are still dominated by short-term profit maximization. The increment in lagged income is more likely to be spent on purchasing more traditional production inputs (fertilizers, pesticides, etc.), leading to a crude growth model of "factor deepening." While this might sustain output and income in the short term, it will continuously exacerbate resource misallocation and environmental pollution, causing a "decoupling" between income growth and RGTFP improvement. The promotional effect of lagged income on RGTFP is significantly weakened and may even become negative due to accumulating environmental costs (Chen et al., 2021). Conversely, when the technology level breaks the critical threshold and enters the high-technology regime, the upgrade in mechanization provides core support for the large-scale application of green technologies. The growth in lagged income equips farmers with the economic capacity to purchase green agricultural machinery (e.g.,

precision seeders, variable-rate fertilization equipment) and complementary green technologies, while a mature mechanization platform can fully unleash the ecological benefits of these technologies (Zhu et al., 2022). For example, mechanized precision operations can significantly reduce redundant fertilizer and pesticide use, and the application of eco-agricultural machinery can enhance the resource utilization of agricultural waste. This creates a virtuous cycle where income growth drives green upgrades in mechanization, achieving synergy between production efficiency and environmental sustainability. At this point, lagged income is no longer confined to additional inputs of traditional factors but is transformed into an enhancement of green production capabilities, thereby significantly strengthening its promotional effect on RGTFP. Therefore, the technology level moderates the direction and intensity of the impact of one-period lagged farmer income on RGTFP by establishing a feasibility threshold for green technology application.

Based on the above, the second and third hypotheses of this study are proposed.

Hypothesis 2: When one-period lagged farmer income is below the threshold, it has a negative impact on RGTFP; when farmer income exceeds the threshold, its promotional effect on RGTFP may be insignificant.

Hypothesis 3: A threshold effect exists for the level of technology. In the low-technology regime, the promotional effect of one-period lagged farmer income on RGTFP is weak or even negative; after surpassing the threshold, the promotional effect of one-period lagged farmer income on RGTFP becomes significant.

IV. Measurement of RGTFP

1. *RGTFP*

Green total factor productivity (GTFP) is an extension of traditional total factor productivity (TFP) within the context of sustainable development. It incorporates negative externalities, such as resource consumption and environmental pollution, into the productivity analysis framework (Ma et al., 2022). Rice green total factor productivity (RGTFP) is the specific application of the GTFP concept to the field of rice production. Its core purpose is to measure the comprehensive efficiency of converting inputs into desirable outputs (e.g., grain yield, ecosystem services) while simultaneously reducing undesirable outputs (e.g., environmental pollution), under the multiple constraints of economic, environmental, and climatic factors.

Distinct from previous research, the RGTFP definition proposed in this study has been expanded in the following three dimensions: (1) We have developed a three-dimensional “climate-economy-ecology” assessment framework that enriches the definition of RGTFP. This framework measures the comprehensive efficiency of maximizing rice yield and carbon sequestration benefits while minimizing GHG emissions, given a set of climatic endowments (non-discretionary factors) and anthropogenic economic inputs (discretionary factors). This definition transcends the traditional two-dimensional “input-output” perspective by internalizing climate variables from their traditional treatment as exogenous factors into “non-discretionary inputs,” thereby more realistically reflecting the natural attributes of agricultural production. (2) This study incorporates the carbon sequestration capacity of the rice production system as a crucial desirable output. Agricultural ecosystems possess the dual attributes of being both carbon sources and carbon sinks, and their net carbon sink effect is a significant positive environmental externality (Yao et al., 2024). By including carbon sequestration alongside rice yield as desirable outputs, the assessment of RGTFP not only reflects economic value but also quantifies the ecological contribution of rice cultivation to mitigating climate change, a dimension seldom addressed in previous studies. (3) We explicitly distinguish between controllable economic inputs, which are determined by human decisions, and climate inputs, which are determined by nature. The former are factors that producers can adjust, such as the costs of fertilizers and labor; the latter are external environmental conditions that decision-makers must accept, such as temperature and precipitation. This distinction allows the measurement model to more accurately isolate productivity growth driven by managerial efficiency and technological progress, rather than attributing it to random fluctuations in climatic conditions.

2. Measurement Methodology

Based on the literature review, the measurement of RGTFP in this study is conducted using the DDF and the GML index. The measurement principles and formulas are as follows:

In this study, each province is defined as a decision-making unit (DMU). Based on a panel dataset consisting of J DMUs ($j = 1, \dots, J$) over T time periods ($t = 1, \dots, T$), each DMU uses N inputs, $x = (x_1, x_2, \dots, x_N)$, to produce M desirable outputs, $y = (y_1, y_2, \dots, y_M)$, and I undesirable outputs, $b = (b_1, b_2, \dots, b_I)$. The

production possibility set (PPS) for a given set of inputs x is defined as: $P(x) = \{(y, b) | x \text{ can produce } (y, b)\}$. Choosing a directional vector $g = (g_y, g_b)$ to simultaneously expand desirable outputs and contract undesirable outputs, the DDF can be written as: $D(x, y, b; g) = \max\{\beta | (y + \beta g_y, b - \beta g_b) \in P(x)\}$. The GML index framework involves two types of PPS. The contemporaneous PPS is constructed from the observational data of all DMUs in a specific period t , representing the best available technology in that period. The DDF calculated with reference to this is denoted as $D^t(x^t, y^t, b^t)$. The global PPS is constructed from the observational data of all DMUs across all time periods, encompassing the technologies of all periods. The DDF calculated with reference to this global PPS is denoted as $D^G(x^t, y^t, b^t)$. Here, the arguments (x^t, y^t, b^t) represent the inputs and outputs of a DMU in period t .

The GML index characterizes the change in productivity by comparing the DDF values of the same DMU in two consecutive periods, t and $t + 1$, relative to the global PPS:

$$RGTFP = GML^{t,t+1} = \frac{1 + D^G(x^t, y^t, b^t)}{1 + D^G(x^{t+1}, y^{t+1}, b^{t+1})} \quad (1)$$

In Equation (1), the value of $GML^{t,t+1} > 1$ indicates an improvement in green productivity. Conversely, the value of $GML^{t,t+1} < 1$ indicates a decline in green productivity.

3. Selection of Measurement Variables

Based on the expanded definition of RGTFP presented earlier, the selection of input and output variables primarily draws upon the research of Gao et al. (2022a), Myeki et al. (2023) and Lu et al. (2025). After considering the feasibility of data acquisition, we constructed a three-dimensional “climate-economy-ecology” assessment framework to estimate the RGTFP for 22 provinces in China. A key distinction from previous research is our use of four monetized anthropogenic inputs from an economic perspective, supplemented by three climate-related variables (non-discretionary inputs). The output side includes rice yield and, notably, the carbon sequestration of the rice production system from an ecological perspective, serving as two desirable outputs. The undesirable output selected is the GHG emissions from rice production, which reflects environmental quality. A value we denote as RGTFPS is calculated

Table 1. Input and Output Variables for the Estimation of Rice Green Total Factor Productivity (RGTFP)

Variable Category	Variable Name	Variable Definition	Data Source
Input	Labor	Includes the imputed cost of family labor and hired labor costs. Unit: 10,000 CNY. (Deflated to 2004 real prices using the rice PPI)	EPS China Agricultural Product Cost-Benefit Database (EPS-CAPCBD)
	Land	Includes the imputed cost of self-owned land and land rental costs. Unit: 10,000 CNY. (Deflated to 2004 real prices using the rice PPI)	EPS-CAPCBD
	Direct Material & Services	Includes costs for seeds, chemical fertilizers, manure, pesticides, agricultural film, rental operations (machinery and animal traction), fuel and power, technical services, tools and materials, repair and maintenance, and other direct expenses. The monetized cost of water input refers to irrigation and drainage fees. Unit: 10,000 CNY. (Deflated to 2004 real prices using the rice PPI)	EPS-CAPCBD
	Indirect Material & Services	Includes depreciation of fixed assets, taxes (until 2005), and costs for insurance, management, finance, and sales. Unit: 10,000 CNY. (Deflated to 2004 real prices using the rice PPI)	EPS-CAPCBD
Non-discretionary Input	Temperature	Average temperature from March to October. Unit: Celsius	Provincial Statistical Yearbooks, 2005-2023 (PSY, 2005-2023)
	Precipitation	Average precipitation from March to October. Unit: Centimeters	PSY, 2005-2023
	Sunshine Duration	Average sunshine duration from March to October. Unit: Hours	PSY, 2005-2023
Desirable Output	Rice Yield	Total rice production of each province in the corresponding year. Unit: 10,000 tons	National Bureau of Statistics Database
	Carbon Sequestration of the Rice Production System	Carbon sequestered in rice straw, grain, and roots, plus the accumulation of soil organic carbon. Measured in CO ₂ equivalent. Unit: 10,000 tons	Estimated based on the methodology detailed below
Undesirable Output	GHG Emissions from the Rice Production	Direct and indirect CO ₂ , CH ₄ , and nitrous oxide (N ₂ O) emissions during the rice production stage. Measured in CO ₂ equivalent. Unit: 10,000 tons	Estimated based on the methodology detailed below

Source: Author's calculation.

without including the three climate variables and will be used for subsequent robustness checks. The specific measurement standards for the input and output variables of rice production are detailed in Table 1.

In Table 1, the estimation of GHG emissions during the rice production stage is based on the life cycle assessment (LCA) method. The emission factors for agricultural materials and energy are referenced from the CLCD-China 0.8 and Ecoinvent 3.8 databases. The emission factor for field CH₄ is based on the *Guidelines for Compiling Provincial Greenhouse Gas Inventories (Trial)*.¹ The emission factor for field nitrous oxide (N₂O) is referenced from Min and Hu (2012). The emission factor for straw burning is referenced from Liu et al. (2011). The estimation method for the carbon sequestration of the rice production system is referenced from Chen et al. (2022) and Wen et al. (2024). The values for grain moisture content, straw carbon uptake coefficient, straw carbon content, and the change in soil organic carbon are referenced from Chen et al. (2022). The values for the harvest index and root-to-shoot ratio are referenced from Wang et al. (2016). The value for soil bulk density is referenced from Li et al. (2020). The data for the depth of the plough layer are referenced from the *Technical Guidelines for Evaluating the Carbon Footprint of Rice (Draft for Comment)*.²

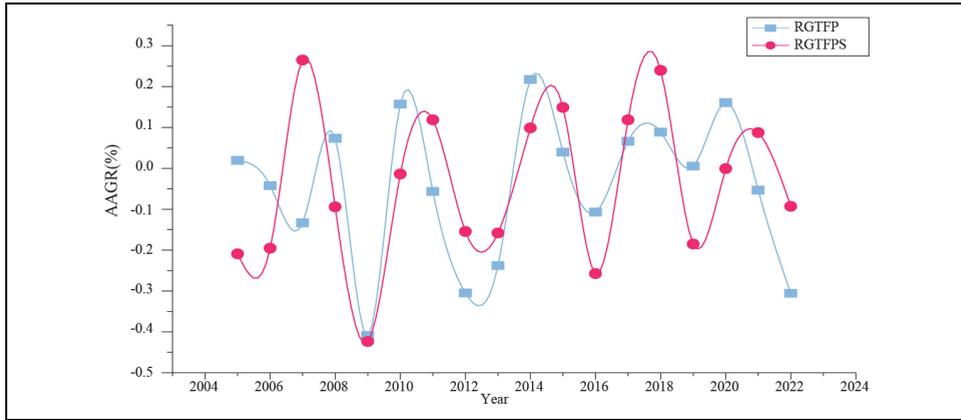
4. Measurement Results

As shown in Figure 1 and Table A1, the annual average growth rate (AAGR) of China's RGTFP exhibits a fluctuating downward trend, with an average annual decrease of 0.046%, and displays distinct characteristics in different periods. From 2005 to 2013, the AAGR of RGTFP showed positive growth only in 2005, 2008, and 2010, while it experienced continuous negative growth from 2011 to 2013. From 2014 to 2020, the AAGR of RGTFP was generally positive, with the exception of 2016. From 2021 to 2022, the AAGR of RGTFP again showed negative growth.

¹ Prepared by experts from relevant institutions under the organization of the Department of Climate Change, National Development & Reform Commission of China, and released in 2011. National Center for Climate Change Strategy and International Cooperation, http://www.ncsc.org.cn/SY/tjkybg/202003/t20200319_769763.shtml.

² Prepared under the leadership of the Institute of Crop Sciences, Chinese Academy of Agricultural Sciences, and completed in 2024. Rural Energy and Environment Agency, Ministry of Agriculture and Rural Affairs, http://www.reea.agri.cn/zhbwh/202404/t20240419_8626471.htm.

Figure 1. Annual Average Growth Rates (AAGR) of RGTFP and RGTFPS in China



Notes: The figure shows the annual average growth rates (AAGR) of two rice green total factor productivity indices. RGTFP is estimated by incorporating climate variables, while RGTFPS is estimated without them.

Source: Author's calculation.

Simultaneously, we find that the AAGR curves for both RGTFP and RGTFPS exhibit no long-term monotonic trend, consistently fluctuating around the zero line. By comparing the RGTFP measured by our “climate-economy-ecology” framework with the RGTFPS calculated without considering climate factors, we arrive at three conclusions. First, conventional models severely underestimate risks in disaster years. In 2007, the Huai River Basin experienced a once-in-a-century flood; from March to May, precipitation in the Songnen and North China Plains was 40-60% below average; and Typhoons Sepat and Rosa triggered heavy rainfall, causing late rice to lodge and farmlands to become waterlogged in southeastern coastal areas, leading to production losses of over 10% in places like Zhangzhou, Fujian, and Wenzhou, Zhejiang. The RGTFP for that year (-0.133%) revealed a 0.398% greater depth of loss compared to the RGTFPS (0.265%). Similarly, during the high-temperature drought event of 2022, RGTFP (-0.31%) revealed a 0.213% greater depth of loss than RGTFPS (-0.09%), exposing the inherent flaw of traditional models that weaken the true impact of extreme climate risks by omitting climate variables. Second, conventional models overestimate green productivity in stable years. In 2018, the RGTFPS estimate (0.24%) was inflated by 0.151% compared to the RGTFP estimate (0.09%); in essence, RGTFPS fails to deduct the exogenous gains in green productivity attributable to favorable climatic conditions. Third, conventional models can lead to a misjudgment of the climate-economy policy disconnect. The asynchronous movements in years like 2007 and 2022

demonstrate that relying solely on RGTFPS would overlook the synergistic necessity of climate adaptation measures and post-disaster economic subsidies. Critically, in 83% of the years, the difference between the AAGR of RGTFP and RGTFPS was greater than 0.1%, and these high-discrepancy values were highly correlated with extreme weather events, revealing that climate variables significantly corrected the assessment results. Therefore, by embedding climate-sensitive parameters, the RGTFP framework avoids underestimating risks in disaster years, curbs the overestimation of contributions in stable years, and promotes climate-economy synergy at the policy level. This provides a core tool that combines scientific completeness with policy operability for the green transformation of agriculture, making it especially indispensable for precise decision-making under the goal of achieving “dual carbon” targets.³

V. The Impact of Farmer Income on RGTFP

1. Study Area

The sample for this study comprises 22 provinces (including autonomous regions and municipalities) in mainland China where the rice planting area exceeded 80,000 hectares in 2022.⁴ The study period spans from 2004 to 2022. This scope was determined for two primary reasons: first, to ensure the sample's representativeness by excluding regions with small-scale rice cultivation; second, because China implemented a direct grain subsidy policy in 2004 (with subsidies totaling approximately 11.6 billion CNY that year), which significantly promoted rice production development.

2. Model Specification and Variable Selection

(1) Benchmark model

To deeply investigate how farmer income drives RGTFP, this study uses the RGTFP of each province as the dependent variable and farmer income as the core

³ On September 22, 2020, China announced that it would aim for its CO₂ emissions to peak before 2030 and strive to achieve carbon neutrality before 2060.

⁴ The specific regions include Hebei, Nei Mongolia, Liaoning, Jilin, Heilongjiang, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong, Henan, Hubei, Hunan, Guangdong, Guangxi, Hainan, Chongqing, Sichuan, Guizhou, Yunnan, and Shaanxi.

independent variable, incorporating several control variables. To align with the dynamic nature of RGTFP and the time lags in producer decision-making, we construct a two-way fixed effects dynamic panel model. This model is estimated using Panel Feasible Generalized Least Squares (PFGLS) to simultaneously address potential issues of cross-sectional heteroskedasticity, cross-sectional dependence, and province-specific autocorrelation. The model is specified as follows:

$$\ln RGTFP_{it} = \beta_0 + \beta_1 \ln RGTFP_{it-1} + \beta_2 FI_{it-1} + \beta_{3k} CV_{kit} + \mu_i + \delta_t + \varepsilon_{it} \quad (2)$$

In Equation (2), $\ln RGTFP_{it}$ denotes the logarithm of rice green total factor productivity. The subscript i indexes provinces, and t indexes years. β_0 is the constant term. FI is the core independent variable, farmer income. CV_{kit} denotes the vector of control variables, with k indexing each control. β_1 , β_2 and β_{3k} are the coefficients to be estimated. μ_i and δ_t denote the individual (province) and time fixed effects, respectively. ε_{it} is the random error term.

(2) Panel threshold model

To examine the potential non-linear relationship, a panel threshold model is introduced. Equation (3) considers a single-threshold model with the core independent variable (FI) as the threshold variable, while Equation (4) considers a single-threshold model using the mechanization level ($Mech$) as the threshold variable. The models are expressed as:

$$\begin{aligned} \ln RGTFP_{it} = & \alpha_0 + \alpha_1 \ln RGTFP_{it-1} + \alpha_2 FI_{it-1} \cdot I(FI_{it-1} \leq \tau) \\ & + \alpha_3 FI_{it-1} \cdot I(FI_{it-1} > \tau) + \alpha_4 CV_{kit} + \mu_i + \delta_t + \varepsilon_{it} \quad (3) \end{aligned}$$

$$\begin{aligned} \ln RGTFP_{it} = & \alpha_0 + \alpha_1 \ln RGTFP_{it-1} + \alpha_2 FI_{it-1} \cdot I(\ln Mech_{it} \leq \tau) \\ & + \alpha_3 FI_{it-1} \cdot I(\ln Mech_{it} > \tau) + \alpha_4 CV_{(K-1)it} + \mu_i + \delta_t + \varepsilon_{it} \quad (4) \end{aligned}$$

In Equations (3) and (4), α_0 is the constant term. $CV_{(K-1)it}$ denotes the set of control variables, which—compared with Equation (3)—excludes the logarithm of the mechanization level, $\ln Mech$. K is the total number of control variables. τ is the threshold value. $I(\cdot)$ is an indicator function that equals 1 if the condition inside the

parentheses holds and 0 otherwise. The coefficients α_1 , α_2 and α_3 are the coefficients on the respective variables. All other variables and terms are defined as in Equation (2).

(3) Variable selection

Dependent Variable: The dependent variable in this study is rice green total factor productivity, denoted as RGTFP. Its value is calculated using the DDF and the GML index, according to Equation (1).

Independent Variable: The core independent variable is the one-period lagged farmer income (FI_{t-1}). We use lagged net profit from rice production as a proxy for lagged farmer income. Net profit is chosen to represent the core independent variable because, in the context of agricultural green transformation decisions, green production practices are often associated with additional input costs and uncertainty risks. Only the net profit, after deducting all expenses, can truly determine whether farmers have the financial capacity and willingness to bear the “green premium” of rice production. Due to a 1–2-year time lag in rice production (“change in farmer income \rightarrow adjustment in input decisions \rightarrow change in RGTFP”), farmers may adjust the following year’s fertilizer and machinery inputs based on the net profit of the previous year or even earlier. This input adjustment’s impact on RGTFP becomes apparent in the subsequent year. Furthermore, the complex interplay of production inertia and policy lags means that lagged net profit can capture the dynamic, cross-cycle adjustment effects. This dynamic mechanism, modeled through a lagged variable, is more consistent with the actual decision-making logic of rice production. Therefore, this proxy variable can reveal how economic incentives ultimately drive changes in RGTFP. Additionally, we use the profit-to-cost ratio (PCR) as an alternative proxy for farmer income for robustness checks.

Threshold Variables: To test for potential threshold effects, two threshold variables are set. First, the core independent variable, one-period lagged farmer income (FI_{t-1}), is selected as the threshold variable (for Equation 3). Second, a proxy for the technology level, the mechanization level ($\ln\text{Mech}$), is used as the threshold variable (for Equation 4).

Control Variables: Drawing from the existing literature (Gao et al., 2022b; Wang et al., 2022; Luo et al., 2023; Zhou et al., 2024; Zhang et al., 2024), this study selects the following eight control variables: (1) Economic scale (Eco): The annual Gross Domestic Product (GDP) of each rice-producing province. (2) Urbanization level

(Urb): The proportion of the urban population to the total population in each province. (3) Industrialization level (Ind): The proportion of industrial value-added to the GDP in each province. (4) Per capita education level of rural residents (Edu): The average years of schooling for the rural population in each province, calculated as: (Number of people with primary education $\times 6$ + junior high $\times 9$ + senior high $\times 12$ + college and above $\times 16$) / Total sample population aged six and above. (5) Fiscal support for agriculture (Fin): The ratio of fiscal expenditure on agriculture, forestry, and water conservancy to the total fiscal expenditure. (6) Crop disaster rate (Dis): The ratio of the crop area affected by disasters to the total sown area of crops. (7) Mechanization level (Mech): A proxy for the technology level, measured as the total power of agricultural machinery per hectare (in kW). A higher value indicates a higher technology level. (8) Fertilizer use intensity (Fer): Measured as the kilograms of chemical fertilizer applied per mu⁵.

(4) Data description

The data sources for estimating the RGTFP are shown in Table 1. To mitigate the impact of large disparities in magnitude, all input and output variables were log-transformed before estimation. The values for RGTFP and RGTFPS are the results calculated using Equation (1). For the variables in the regression model, the data for the proxies of farmer income (net profit and profit-to-cost ratio) were obtained from the EPS China Agricultural Product Cost-Benefit Database. Data for economic scale, urbanization level, industrialization level, per capita education level of rural residents, fiscal support for agriculture, crop disaster rate, mechanization level, and fertilizer use intensity were sourced from the *China Statistical Yearbook* and the statistical yearbooks of the respective provinces. A multiple imputation method was used to fill in any individual missing data points. Net profit and economic scale were deflated using 2004 as the base period. The former was converted from nominal to real comparable prices using the rice production price index, while the latter was converted using the regional GDP index (previous year = 100). The descriptive statistics of the variables are presented in Table 2. To reduce the interference of outliers, all variables were winsorized at the 1st and 99th percentiles.

⁵ “Mu” is a traditional Chinese unit of land area commonly used in agricultural production, with one mu being equivalent to approximately 666.667 square meters.

Table 2. Descriptive Statistics

Variable	N	Mean	SD	Min	Median	Max
RGTFP	396	0.9995	0.0063	0.9755	1.0000	1.0260
RGTFPS	396	0.9996	0.0091	0.9504	0.9995	1.0632
FI	396	2220.477	2117.565	-3475.725	2284.8	9710.337
PCR	418	24.3474	25.3152	-23.4600	21.9543	129.4900
Eco	418	8308.4368	5973.9279	810.9502	6489.6005	28500
Urb	418	0.5323	0.1100	0.2628	0.5388	0.7478
Ind	418	0.3595	0.0798	0.1001	0.3637	0.5423
Edu	418	8.7335	0.7627	6.3778	8.7800	10.2315
Fin	418	0.1059	0.0280	0.0453	0.1081	0.1897
Dis	418	0.1839	0.1396	0.0042	0.1544	0.9359
Mech	418	5.7028	2.2642	1.6979	5.2985	12.7037
Fer	418	22.1579	5.8937	10.4237	21.5853	39.6200

Source: Author's calculation.

3. Empirical Results and Analysis

To examine the impact of farmer income on RGTFP, this study employs a progressive analytical framework, moving from a model without control variables to one with control variables, to test the stability of the core relationship. The regression results are presented in Table 3.

As shown in Table 3, the core independent variable—one-period lagged farmer income (L.FI)—has a significant negative impact on lnGRFTP in both model specifications. The statistical significance is maintained at the 1% level in both cases. In the model without control variables (Column 1), the coefficient of L.zFI (the standardized form of L.FI) is -0.0011. After including control variables (Column 2), the absolute value of the coefficient increases to 0.0014, suggesting that omitting control variables may underestimate the inhibitory effect of farmer income on RGTFP. This result indicates that for every one-unit increase in lagged net profit from rice production, the current RGTFP decreases by an average of 0.14%. This finding, while seemingly contrary to the intuition of an “income-driven green transition,” actually reflects a “short-term profit-seeking lock-in” in China's rice production during the sample period. Under the current “yield-first” market pricing mechanism, farmers, in order to boost immediate returns, tend to excessively apply fertilizers and pesticides. Meanwhile, insufficient mechanization during the sample period may have further

constrained the adoption of green technologies. This ultimately forms a vicious cycle of “income growth → resource misallocation → RGTFP decline,” which hinders the enhancement of RGTFP. This validates Hypothesis 1.

The coefficient of the lagged dependent variable $L.\ln\text{RGTFP}$, (the one-period lagged form of $\ln\text{RGTFP}$), is -0.3339 , reflecting that RGTFP possesses dynamic adjustment characteristics. Specifically, the previous period’s RGTFP level has a negative spillover effect on the current period.

To eliminate interference from measurement errors, model specification bias, and the choice of proxy variables for the core variable, this study conducts robustness checks from three dimensions: “substituting the dependent variable,” “changing the proxy for the core independent variable,” and “adjusting the estimation method.” The results are presented in columns (3), (4), and (5) of Table 3. First, substituting the dependent variable. We use RGTFP with climate factors removed ($\ln\text{RGTFPS}$, the logarithmic form of RGTFPS) as the alternative dependent variable. As shown in Table 3 (Column 3), the coefficient of $L.z\text{FI}$ remains -0.0014 , which is identical to the baseline regression coefficient and significant at the 1% level. This confirms that the inhibitory effect of farmer income on RGTFP remains robust. Second, changing the proxy for the core independent variable. We use the one-period lagged profit-to-cost ratio per mu of rice production ($L.z\text{PCR}$, the one-period lagged and standardized form of PCR) as the alternative proxy for farmer income. Compared to net profit, profit-to-cost ratio better reflects the relationship between income and production costs and can avoid biases from absolute income fluctuations. Table 3 (Column 4) shows that the coefficient of $L.z\text{PCR}$ is -0.0015 , which is consistent in sign and similar in magnitude to the baseline result. This indicates that the core conclusion is not affected by the measurement method of the income indicator. Third, adjusting the estimation method. Considering that the RGTFP values are concentrated around 1, which may exhibit characteristics of a censored distribution, this study re-estimates the baseline equation using a Tobit model, as shown in Table 3 (Column 5). The results show that the coefficient of $L.z\text{FI}$ is -0.0023 , still maintaining a significant negative impact. This demonstrates that adjusting the estimation method does not alter the core relationship, and the baseline conclusion is methodologically robust. In summary, the consistent results from these three dimensions of robustness checks confirm the reliability of the conclusion that farmer income has a significant inhibitory effect on RGTFP.

An endogeneity problem may exist between farmer income and RGTFP, which could lead to biased baseline regression results. To address this issue, this study

employs the System Generalized Method of Moments (System GMM) for endogeneity correction. The results are presented in Table 3 (Column 6). We use lags 1-2 of the dependent variable (lnRGTFP) and lags 2-3 of the core independent variable (L.zFI) as instrumental variables (IVs). The results show that after correcting for endogeneity, the impact of the core independent variable L.zFI on lnRGTFP remains significantly negative: the coefficient of L.zFI is -0.0034, implying that a one-unit increase in farmer income leads to a significant 0.34% decrease in RGTFP. This result further validates the core conclusion that farmer income has a significant inhibitory effect on RGTFP.

Table 3. Baseline Regression Results and Robustness Checks

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	lnRGTFP	lnRGTFP	lnRGTFPS	FI-PCR	Tobit	System GMM
L.zFI	-0.0011*** (0.0002)	-0.0014*** (0.0003)	-0.0014*** (0.0004)		-0.0023*** (0.0009)	-0.0034** (0.001)
L.zPCR				-0.0015*** (0.0003)		
L.lnRGTFP	-0.3427*** (0.0466)	-0.3339*** (0.0453)	-0.1849*** (0.0385)	-0.3367*** (0.0462)	-0.2708*** (0.0714)	-0.1733* (0.088)
cons	-0.0008 (0.0013)	0.0675*** (0.0252)	0.0000 (0.0000)	0.0706*** (0.0237)	0.0675 (0.0653)	-0.0147 (0.014)
Province fixed	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes	Yes	Yes
Controls	NO	Yes	Yes	Yes	Yes	Yes
N	396	374	374	374	374	374
Wald χ^2	559867.66	29890.78	104504.89	41185.78		
AR (1) (p-value)						0.003
AR (2) (p-value)						0.393
Hansen J (p-value)						0.444

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

a. Columns (1)-(4) are estimated with PFGLS, controlling for province and year fixed effects, AR (1) autocorrelation, and heteroskedasticity.

b. Column (5) is a panel Tobit model.

c. Column (6) is a Two-step system GMM with robust standard errors.

Source: Author's calculation.

4. Threshold Effect Analysis

This study uses one-period lagged farmer income (L.zFI) and the level of mechanization (lnMech) as threshold variables to test for non-linear characteristics in the impact of farmer income on RGTFP. We employ the dynamic panel threshold models specified in Equations (3) and (4) to test for the existence of a threshold effect. First, one-period lagged farmer income and the level of mechanization are set as threshold variables. We use the bootstrap method to test the significance and number of thresholds, with the number of bootstrap replications set to 1000 and the number of grid points set to 400. The threshold significance test and estimation results are shown in Table 4, and the interval regression results are presented in Table 5.

The threshold significance test results in Table 4 indicate that with L.zFI as the threshold variable, the F-statistic for a single threshold is 7.27 ($p=0.0310$), which is significant at the 5% level. The F-statistic for a double threshold is 7.06 ($p=0.1610$), which is not significant. With lnMech as the threshold variable, the F-statistic for a single threshold is 9.70 ($p=0.0320$), significant at the 5% level, while the F-statistic for a double threshold is 1.11 ($p=0.9580$), which is not significant. These results confirm that both farmer income and the level of mechanization have a single threshold effect on RGTFP.

Table 5 shows that the estimated single threshold value for L.zFI is -0.6437 , corresponding to an actual income of 857.4 CNY/ha (95% confidence interval: $[-0.6446, -0.6428]$). This figure is close to the break-even point for smallholders in most of China's major rice-producing areas (according to the Ministry of Agriculture and Rural Affairs' annual *National Agricultural Product Cost-Benefit Data Compilation*, the net profit per hectare of rice fluctuated mainly between 450–1200 CNY from 2010–2020). This threshold can be seen as the critical point where farmers shift from a “survival-oriented” mindset to “possessing the capacity for green transition.” The sample is accordingly divided into two regimes: (1) Low-Income Regime ($L.zFI \leq -0.6437$, actual income ≤ 857.4 CNY/ha, 30.21% of the sample): The coefficient of L.zFI is -0.0023 ($p=0.012$), which is significantly negative. In this stage, farmers prioritize ensuring their livelihood and are in a “survival-priority” state. Their tolerance for the high costs of green technology is extremely low, and they tend to increase yields by excessively applying low-cost chemical inputs, thus exacerbating the inhibition of RGTFP. (2) Medium-to-High-Income Regime ($L.zFI > -0.6437$, 69.79% of the sample): The coefficient turns positive to 0.0004 but is not significant ($p=0.668$). This suggests

Table 4. Threshold Effect Test and Estimation Results

Dependent Variable (Threshold)	Type	Threshold Value	F-Value	P-Value	95% Confidence Intervals	BS Number
lnRGTFP (L.zFI)	Single Threshold	-0.6437	7.27**	0.0310	[-0.6446, -0.6428]	1000
	Double Threshold (First)	-0.1427	7.06	0.1610	[-0.2271, -0.1403]	1000
	Double Threshold (Second)	0.4767	7.06	0.1610	[0.4731, 0.4884]	1000
lnRGTFP (lnMech)	Single Threshold	1.8153	9.70**	0.0320	[1.6861, 1.8227]	1000
	Double Threshold (First)	1.8153	1.11	0.9580	[1.6861, 1.8227]	1000
	Double Threshold (Second)	1.3761	1.11	0.9580	[1.3717, 1.3799]	1000

Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Source: Author's calculation.

Table 5. Double-Threshold Model Results

Dependent Variable	Threshold Interval	Coefficient	Standard Error	P-Value	95% Confidence Interval
lnRGTFP	L.zFI ≤ -0.6437	-0.0023**	0.0008	0.012	[-0.0040, -0.0005]
	-0.6437 < L.zFI	0.0004	0.0095	0.6680	[-0.0016, 0.0024]
lnRGTFP	lnMech ≤ 1.8153	-0.0001	0.0006	0.8720	[-0.0014, 0.0012]
	1.8153 < lnMech	0.0023**	0.0010	0.0240	[0.0003, 0.0043]

Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Source: Author's calculation.

that medium-to-high income provides farmers with the latent capacity for a green transition. However, the potential may not be realized in this regime, possibly because the price premium for green rice is insufficient and the coverage of agricultural technology extension services is low, thus masking the significance of the positive effect. This validates Hypothesis 2.

The estimated single threshold value for the level of mechanization (lnMech) is 1.8153, corresponding to an actual mechanization level of 6.14 kW/ha (95% confidence interval: [1.6861, 1.8227]). The sample is accordingly divided into two regimes: (1) Low-Mechanization Regime (lnMech ≤ 1.8153, 58.47% of the sample): The coefficient of L.zFI is -0.0001 (p=0.8720) and is statistically insignificant. When the mechanization level is low, farmers lack the tools for precise input application, and income growth cannot be effectively translated into RGTFP improvement. (2) High-Mechanization Regime (lnMech > 1.8153, 41.53% of the sample): The coefficient is

0.0023 ($p=0.024$) and is significantly positive. Furthermore, data from the *China Agricultural Machinery Industry Yearbook* shows that mechanization levels reach over 15.0 kW/ha in the Northeast China Plain, while in hilly regions they are often below 4.5 kW/ha. The 6.14 kW/ha threshold is precisely the critical node for transitioning from “traditional labor + simple machinery” to “comprehensive and intelligent agricultural machinery.” This indicates that high mechanization reduces the reliance on chemical inputs by optimizing factor allocation, thereby reversing the inhibitory effect of income and promoting RGTFP growth. This confirms that the level of mechanization serves as a core bridge in the “income–green transition” nexus. Its role in optimizing factor allocation through practices like precision fertilization and straw incorporation complements the findings of Zhu et al. (2022) that “mechanization enhances agricultural GTFP.” However, our study further quantifies the critical threshold, specifying that mechanization must exceed 6.14 kW/ha to reverse the inhibitory effect of income, providing a quantitative basis for policy intervention. This validates Hypothesis 3.

In summary, the low-income and low-mechanization regimes combine to form a “Trap Zone.” Faced with both survival pressure and the absence of a technological platform, farmers are stuck in a “low-end lock-in” state, causing their income to have a negative impact on RGTFP. The low-income and high-mechanization regimes constitute a “Potential Zone.” Although a technological platform is available, it is constrained by insufficient capital, leading to an insignificant or negative impact of farmer income. The high-income and low-mechanization regimes form a “Bottleneck Zone.” Although capital is available, the lack of a technological platform to leverage it creates a technical bottleneck, rendering the impact of farmer income insignificant. Finally, the high-income and high-mechanization regimes jointly create a “Leading Zone.” By overcoming the dual hurdles of capital and technology, this represents the realistic pathway for achieving a green transition in the sample period, causing farmer income to have a significant positive impact on RGTFP.

VI. Conclusion

Using dynamic panel and threshold models, this study systematically analyzes the impact of farmer income on RGTFP based on data from 22 major rice-producing provinces in China from 2005 to 2022. The core conclusions are as follows:

First, farmer income exhibits a significant linear inhibitory effect on RGTFP. The coefficient of one-period lagged farmer income (L.zFI) on lnRGTFP is significantly negative, and this baseline regression result is robust. It indicates that for every one-unit increase in net profit from rice production, RGTFP decreases by an average of 0.14%. This effect stems from a “yield-first” market orientation combined with production constraints from insufficient mechanization, which leads farmers to pursue short-term profits by overusing chemical inputs, resulting in resource misallocation. This finding reveals the current situation where farmers prioritize short-term profits over long-term technological investment and efficiency improvements, highlighting the existence of an “income trap.” It underscores the importance of shifting farmers’ perspectives to upgrade rice production towards a model of “high yields, low emissions, and high efficiency.”

Second, the impact of income on RGTFP is subject to two distinct single-threshold effects. When farmer income serves as the threshold variable, the critical value is 857.4 CNY/ha. In the low-income regime below this value (30.21% of the sample), the inhibitory effect is strongest; after crossing the threshold, the effect becomes insignificantly positive. When the level of mechanization is the threshold variable, the critical value is 6.14 kW/ha. In the low-mechanization regime below this value (58.47% of the sample), income has no significant effect; after crossing the threshold, the effect turns significantly positive. This demonstrates that medium-to-high income and a high level of mechanization are necessary conditions for farmer income to be converted into a driving force for green transition.

Finally, this study has limitations. Although provincial-level panel data can capture macroeconomic trends, it struggles to reveal differences in decision-making at the individual farm household level. For example, smallholders may be more inclined to maintain traditional production habits after an income increase, whereas new-type agricultural business entities might increase green investments. This behavioral divergence is not adequately captured in our analysis. In future research, we will collect and use farm-household-level data through several years of investigation to further reveal these individual decision-making differences.

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APPENDIX

Table A1. Annual Average Growth Rates (AAGR, %) of RGTFP and RGTFPS in China

Year	RGTFP	RGTFPS
2005	0.0194	-0.2093
2006	-0.04246	-0.1954
2007	-0.13342	0.2649
2008	0.0734	-0.0943
2009	-0.4093	-0.4237
2010	0.157	-0.0139
2011	-0.05671	0.1187
2012	-0.30498	-0.1545
2013	-0.23777	-0.1582
2014	0.2172	0.0989
2015	0.0394	0.1490
2016	-0.10687	-0.2576
2017	0.0662	0.1186
2018	0.0886	0.2397
2019	0.0054	-0.1851
2020	0.1607	-0.0006
2021	-0.05329	0.0874
2022	-0.30569	-0.0931
2005-2013	-0.10387	-0.0962
2014-2022	0.012406	0.0175
2005-2022	-0.04573	-0.0394

Note: The table shows the annual average growth rates (AAGR, %) of two rice green total factor productivity indices. RGTFP is estimated by incorporating climate variables, while RGTFPS is estimated without them.

Source: Author's calculation.